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Lisowska, Anna ; Rekik, Islem

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Predicting Emotional Intelligence Scores From Multi-Session Functional Brain Connectomes

Anna Lisowska[1] and Islem Rekik[2*]

[1] Department of Computer Science, University of Warwick, Coventry, UK
[2]BASIRA lab, CVIP group, School of Science and Engineering, Computing, University of Dundee, UK

Abstract. In this study, we aim to predict emotional intelligence scores from functional connectivity data acquired at different timepoints. To enhance the generalizability of the proposed predictive model to new data and accurate identification of most relevant neural correlates with different facets of the human intelligence, we propose a joint support vector machine and support vector regression (SVM + SVR) model. Specifically, we first identify most discriminative connections between subjects with high vs low emotional intelligence scores in the SVM step and then perform a multi-variate linear regression using these connections to predict the target emotional intelligence score in the SVR step. Our method outperformed existing methods including the Connectome-based Predictive Model (CPM) using functional connectivity data simultaneously acquired with the intelligence scores. The most predictive connections of intelligence included brain regions involved in processing of emotions and social behaviour.

1 Introduction

Understanding how intelligence is encoded in the human brain wiring can help boost the brain cognitive ability in solving new problems and build a more resilient cognitive reserve to neurological disorders. Recently, there has been an increasing interest in the emotional intelligence, which is defined as the ability to monitor emotions (in self and others) to guide one's thinking and behaviour [1]. Emotional intelligence was also associated with job-related, academic and life performance [2].

However, characterising the underlying brain connectivity associated with emotional intelligence remains challenging. Some attempts have been made to identify differences in the brain wiring based on statistical comparison between groups of individuals with dissimilar behavioural scores. While typical correlation and regression analyses are able to model the given dataset well, they lack generalizability. In other words, neural correlates discovered to be significant in predicting intelligence from the connectomic data may not be universal, i.e. applicable to the general population. [3] proposed a Connectome-based Predictive

* Corresponding author: irekik@dundee.ac.uk, www.basira-lab.com

Model (CPM); a cross-validated predictive model, which infers the presence of brain-behaviour relationship on a training data and evaluates its performance on the test data, leading to a more robust and generalizable approach.

In their proposed framework, first, the functional connections that are significantly correlated with the behavioural score are identified using training data. These connections are divided into positively and negatively correlated with the behavioural score. Then, the strengths of significantly correlated connections are summed up for the positively and negatively correlated data, obtaining scalar values for each subject. Finally, a linear regression model is built for positively and negatively correlated features and for the combination of the two. These models are then applied to the test subjects to infer their behavioural scores. The main limitation of this work is that it sums up all positively (resp. negatively) correlated connections with the target behavioral score to create a positive (resp. negative) model. However, each sum may derive from brain connection strengths of different signs (i.e., negative or positive functional connectivity), thereby loosing interpretability of *signed* functional brain connectivitivies that might be associated with the target score.

To address the above limitations, we propose a joint SVM+SVR method to predict behaviour scores from connectomic data by first using a Support Vector Machine (SVM) to identify features which maximally separate the training data into subsets with high and low behavioural scores, thereby enabling a better representation of subjects with extreme scores. Next, we use these features to build a multi-variate regression model using Support Vector Regressor (SVR), which encourages model simplicity for a better generalizability on new data and easy utilizabiliy by clinicians. Further, we identify the top most relevant connections that are associated with different intelligence scores. Additionally, we consider multi-session (or longitudinal) connectomic data for our analysis to investigate the importance of gathering neuroimaging and behavioural data in close time proximity.

2 Methods

In this section we introduce our proposed framework to predict multiple emotional intelligence scores based on the multi-session functional connectivity data (**Fig.** 1). Each subject s is represented by a functional connectivity matrix $\mathbf{X}$ estimated from functional magnetic resonance (fMRI) scans performed at t different timepoints and an intelligence score vector $\mathbf{b} = \{b_1, \ldots, b_N\}$ recorded at a single timepoint t. We first build our model using functional connectivity data obtained at $t = t_1$. Since the functional brain connectivity matrices are symmetric (**Fig.** 1–A), we extract features from each connectivity matrix by directly concatenating the weights of all connectivities in each off-diagonal upper triangular matrix. For each network of size $n \times n$, we extract a feature vector of size $(n \times (n-1)/2)$, where each entry represents the strength of functional connection between two brain regions. This creates a high dimensional feature vector for each subject, which is particularly problematic in training a model that aims to

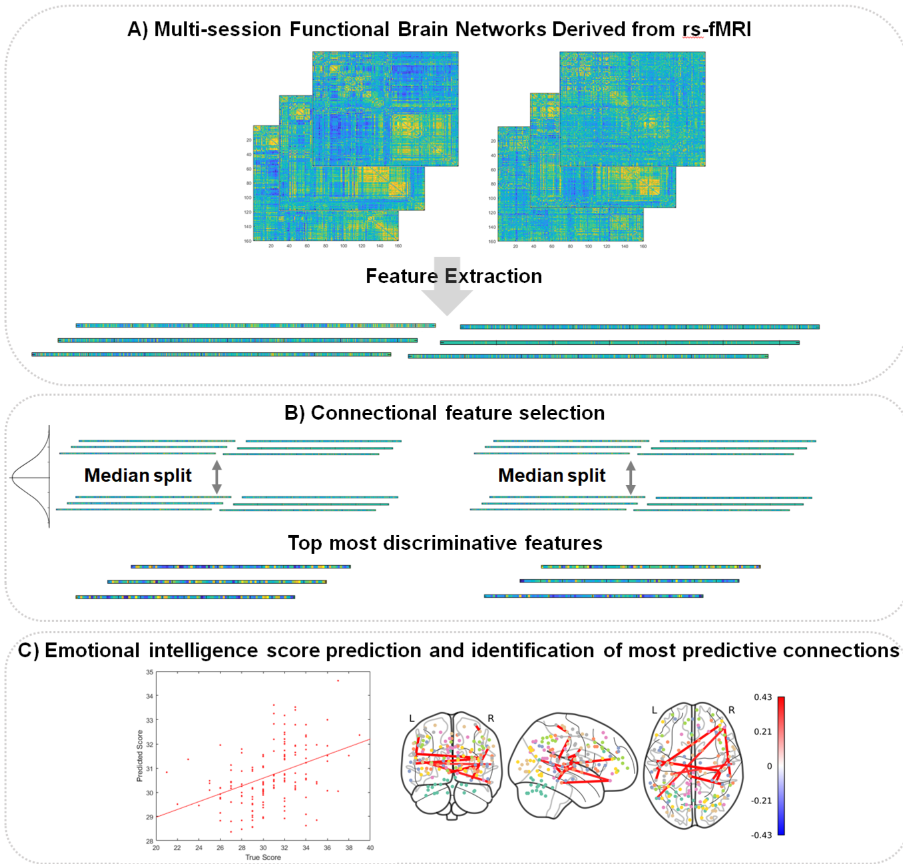

Fig. 1: *Pipeline of the proposed joint SVM+SVR framework to predict emotional intelligence scores from the functional brain connectivity* (A) Functional brain network construction using multi-session fMRI. (B) In the feature selection step, features are ranked according to their contribution to class separability between subjects with high emotional intelligence score and subjects with low emotional intelligence score using training data split at median value of the behavioural score. (C) We use these features to predict the emotional intelligence score of the left-out testing subject within a leave-one-out cross-validation and identify the most predictive functional connections.

map a high-dimensional feature vector into a single score. To address this issue, a feature selection method is required for dimensionality reduction, that would preserve the most informative features, while avoiding underrepresentation of subjects with behavioural scores at both tails of sample distribution.

Therefore, in our joint SVM+SVR framework, the features which maximise the separation of subjects with low scores from subjects with high scores are first identified. In the SVM step, a feature selection is used, which ranks features according to their contribution to class separability (**Fig.** 1–B). As a class separability criterion, we use the area under the ROC curve and identify the features which contribute most to maximising the area. Since this approach requires data to be divided into 2 classes, we define a class with low intelligence scores and high intelligence scores based on median split of the training data ($\leq median$ or $< median$, whichever gives a more balanced split) based on each behavioural score b in $\mathbf{b}$ separately (**Fig.** 1–B).

Once the top most discriminative features are identified in the SVM step using training data, these features can be used to build a predictive model by training the SVR. As the performance of the regression model heavily depends on the number of features used, we vary the number of input features for the SVR model, i.e. multiple models are built, each using different number of input features previously identified in the SVM step.

In the test step, the top features identified in the SVM step are used for the test data and then the intelligence score of the test subjects is predicted using multiple SVR models, each using a different number of input features. At the end of the test stage, the performance of the joint SVM+SVR model is assessed by computing the correlation between the predicted scores and the true emotional intelligence scores of all the test subjects (**Fig.** 1–C). Connections most predictive of the emotional intelligence are identified based on features identified in the model with the best predictive performance. We applied the same steps for each emotional intelligence score in $\mathbf{b}$ using functional connectivity data at each available timepoint t.

3 Results and Discussion

Evaluation dataset We used leave-one-out (LOO) cross validation to evaluate our proposed framework on 149 subjects (74 males, and 75 females, all within 17-27 age range) with structural and functional MRIs using SLIM Dataset [4]. Each MRI is parcellated into 160 regions of interest (ROIs) using Dosenbach Atlas [5]. For each subject, a 160×160 functional connectivity matrix is constructed from fMRI scans at 2 different timepoints: session 1 taking place at the same time as the behavioural assessment and session 2 after 304 days interval on average. Each entry in the connectivity matrix denotes the correlation between mean blood oxygenation level-dependent (BOLD) signals measured in two ROIs. For each subject four emotional intelligence scores are measured: (1) Monitor of Emotions, (2) Social Ability, (3) Appraisal of Emotions, and (4) Utilization of Emotions, as assessed by Schutte Self-Report Emotional Intelligence Scale [6].

Comparison methods and evaluation. For the regression task, we benchmarked our joint SVM+SVR method against: (1) CPM [3] and (2) Correlational SVR, which performs multi-variate linear regression using SVR on features having the most statistically significant correlation with the emotional intelligence score.

For evaluation, we report the R-score, representing the strength of the correlation between the predicted score and the true intelligence score. Since, the performance of regression models heavily depends on the number of input fea-

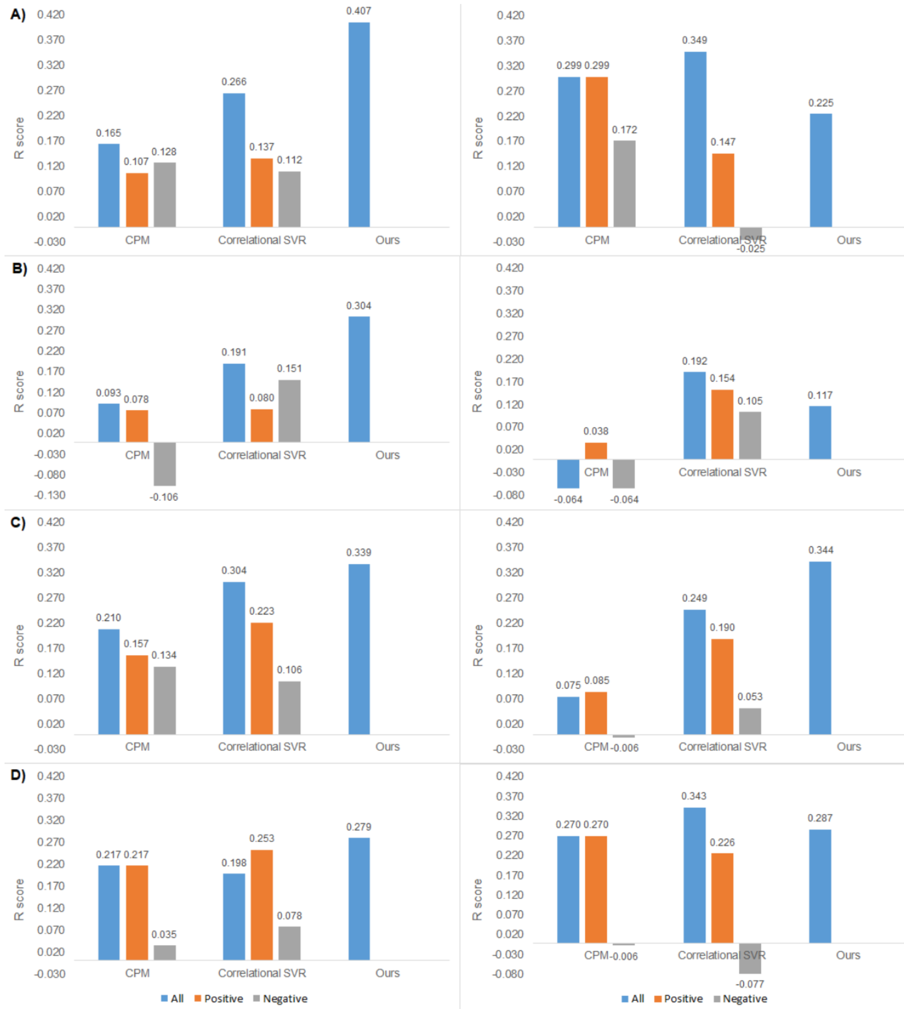

Fig. 2: *R-scores of our proposed joint SVM+SVR model and comparison regression models.* Left: Session 1. Right: Session 2. (A) Monitor of Emotions. (B) Social Ability. (C) Appraisal of Emotions. (D) Utilization of Emotions. Ours: joint SVM+SVR model. Correlational SVR: SVR using features, which are the most significantly correlated with the target emotional intelligence score. CPM [3]: univariate regression model using the sum of all the connections that are significantly correlated with the target emotional intelligence score. All: the model is build using connections that are positively and negatively correlated with the target emotional intelligence score. Positive: only connections that are positively correlated. Negative: Only connections that are negatively correlated.

tures, for the joint SVR+SVR method and for the correlational SVR, we chose a range of input features 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, 80, 90, 100, 125, 150, 175, 200, 300, 400, 500, 600, 700, 800, 900, 1000 to train the model.

For the joint SVM+SVR, the identified features were ranked highest based on their contribution to the area under the ROC curve in the SVM classification task. For the correlational SVR method, features that were most significantly correlated with the target behavioural score were selected. Since CPM [3] used all features significantly correlated with the target score instead of choosing different number of features, we addressed this limitation by exploring the range of statistical significance thresholds in $\{0.1, 0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001\}$ and used all significant features *at a given threshold* for the regression analysis using CPM model [3]. For evaluation, we report the top R-score obtained across different feature numbers (for joint SVM+SVR and correlational SVR) or significance thresholds (for CPM [3]). **Fig.** 2 shows the comparison between R-scores obtained using our method and the benchmark methods for the four different emotional intelligence scores using functional connectome data from sessions 1 and 2.

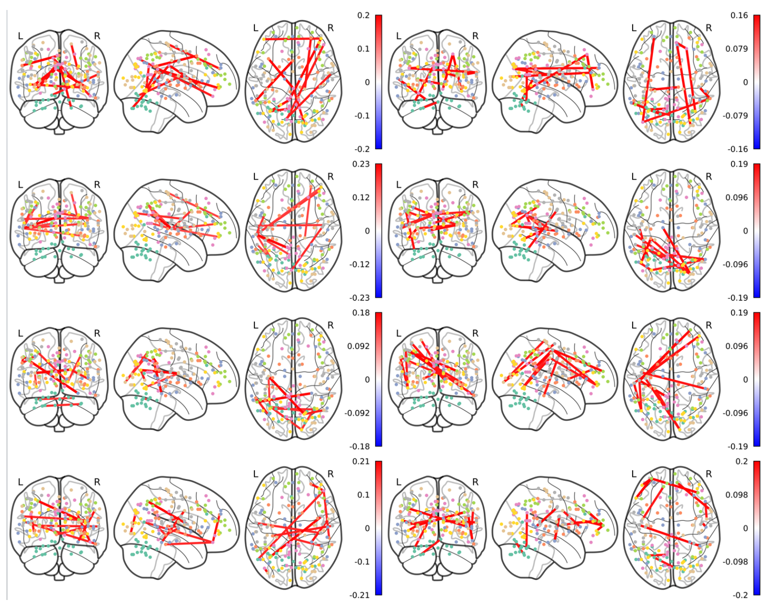

Fig. 3: *The top 10 connections disentangling subjects with high emotional intelligence scores and subjects with low scores.* Left: Session 1. Right: Session 2. (A) Utilization of Emotions. (B) Appraisal of Emotions. (C) Social Ability. (D) Monitor of Emotions.

Our method outperformed benchmark methods in predicting all the emotional intelligence scores using functional connectivity data from Session 1 of fMRI acquisition (**Fig.** 2). This was not the case for Session 2, where the correlational SVR performed best for the Utilization of Emotions **Fig.** 2–D, Social Ability **Fig.** 2–B and Monitor of Emotions **Fig.** 2–A, but not the Appraisal of Emotions **Fig.** 2–C, for which our method still performed best. Our method generally gave better results using a lower number of features as compared to the benchmark methods. It should be noted that the performance of the joint SVM+SVR heavily depends on the training data distribution and the way the data is split into classes. The more separable the subjects with high intelligence scores are from the subjects with low intelligence scores, the bigger is the area under the ROC curve obtained in the SVM classfication step. Hence, the more separable the data is in the SVM step, the better is the SVR prediction performance.

Identified functional brain connections fingerprinting intelligence.

Our findings. For each emotional intelligence score using functional connectivity from Session 1 and Session 2, we identified the top 10 features with the highest average rank across subjects. The most predictive connections were identified based on the features used for predicting the emotional intelligence score resulting in the best R-score. **Fig.** 3 displays the top 10 features identified by the joint SVM+SVR for each emotional intelligence score. Top most predictive connections, that involved common brain regions across all the emotional intelligence scores, included mid insula, basal ganglia, post cingulate, ventral anterior prefrontal cortex and occipital lobe.

Insular cortex was proposed to facilitate social interaction and decision-making by integrating information about uncertainty with sensory, affective and bodily information [7]. Consistent with our findings, studies on insular lesion found that insula plays role in emotional intelligence [8]. Further, basal ganglia is involved in reward-stimulus processing and goal-directed bahaviour, specifically the subthalamic nucleus was suggected to integrate motor, congnitive and emotional aspects of behaviour [9]. While the cingulate gyrus plays a role in pain and emotion processing and a lesion study by [10] found decreased social interactions and time spent with other individuals, showing role of cingulate in emotion and social behaviour. The anterior prefrontal cortex is important for emotional control during social interactions. In their study, [11] showed that the anterior prefrontal cortex is required for coordination of action selection, emotional conflict detection and inhibition of emotionally-driven responses.

Furthermore, connections to the occipital cortex were found to be a significant predictor in case of all the emotional intelligence scores. This could be explained by aspects uncontrolled for in the rs-fMRI data acquisition step, such as low-frequency fluctuations occurring synchronously in functionally connected brain regions, present especially in auditory, visual and motor areas [12]. However, some evidence exist for occipital lobe's role in emotional information processing [13].

Variability of discovered intelligence connectivity trends across scores and sessions. In our analysis, we found that the connections that are most predictive of the emotional inteligence scores are largely inconsistent between the two sessions (**Fig.** 3). Given that fMRI for Session 2 was performed on average 304 days after Session 1, one could expect some changes in the individual's functional connectivity. One explanation could be the difference in the conditions under which the fMRI was aquired and the general instability of the functional data [14].

In **Fig.** 2 the performance of the joint SVM+SVR model in predicting different emotional intelligence scores using a subset of connecions identified from the functional connectivity data aquired during Session 1 and Session 2 can be seen. While using a subset of connections from the functional connectivity data from Session 1, collected at the same time as the intelligence scores, gave better predictions for Monitor of Emotions and Social Ability, the connections chosen by the joint SVM+SVR to predict the Appraisal of Emotions and Utilization of Emotions perform similarly well using the functional data from Session 1 and Session 2. It is possible that the Monitor of Emotions and the Social Ability and their underlying neural correlates are more prone to changes over time than the Appraisal of Emotions and Utilization of Emotions, which emphasises the need to acquire fMRI data at the same time as intelligence scores for accurate predictions. This should be further investigated. Since a reasonable predictive power is obtained for the majority of intelligence scores using functional connectivity data from both Session 1 and Session 2, it is possible that the longitudinal data contains complementary information. Further studies could combine the functional data from different timepoints to predict the target intelligence scores as in [15], where a multi-task multi-linear regression model was proposed to predict infant cognitive scores from longitudinal neuroimaging data. For a more holistic investigation of the brain intelligence construct, we will include morphological brain networks [16, 17] and structural networks [18, 19] into our future brain-intelligence analyses.

4 Conclusion

We proposed a joint SVM+SVR model to predict emotional intelligence of individuals from their functional connectomic data. Our method outperformed the benchmark methods using functional data acquired at the same time as the target scores. The joint SVM+SVR benefits from model simplicity and interpretability, which is of particular interest for clinicians. Functional brain connections associated with intelligence identified by our model belonged to brain regions involved in emotion processing and social behaviour, consistent with previous research. Further studies could combine functional data acquired at different timepoints for improved emotional intelligence predictions.

References

1. Salovey, P., Mayer, J.D.: Emotional intelligence. Imagination, cognition and personality **9** (1990) 185–211
2. Van Rooy, D.L., Viswesvaran, C.: Emotional intelligence: A meta-analytic investigation of predictive validity and nomological net. Journal of vocational Behavior **65** (2004) 71–95
3. Shen, X., Finn, E.S., Scheinost, D., Rosenberg, M.D., Chun, M.M., Papademetris, X., Constable, R.T.: Using connectome-based predictive modeling to predict individual behavior from brain connectivity. nature protocols **12** (2017) 506

4. Liu, W., Wei, D., Chen, Q., Yang, W., Meng, J., Wu, G., Bi, T., Zhang, Q., Zuo, X.N., Qiu, J.: Longitudinal test-retest neuroimaging data from healthy young adults in southwest china. Scientific data **4** (2017) 170017
5. Dosenbach, N.U., Nardos, B., Cohen, A.L., Fair, D.A., Power, J.D., Church, J.A., Nelson, S.M., Wig, G.S., Vogel, A.C., Lessov-Schlaggar, C.N., et al.: Prediction of individual brain maturity using fmri. Science **329** (2010) 1358–1361
6. Schutte, N.S., Malouff, J.M., Hall, L.E., Haggerty, D.J., Cooper, J.T., Golden, C.J., Dornheim, L.: Development and validation of a measure of emotional intelligence. Personality and individual differences **25** (1998) 167–177
7. Singer, T., Critchley, H.D., Preuschoff, K.: A common role of insula in feelings, empathy and uncertainty. Trends in cognitive sciences **13** (2009) 334–340
8. Bar-On, R., Tranel, D., Denburg, N.L., Bechara, A.: Exploring the neurological substrate of emotional and social intelligence. Brain **126** (2003) 1790–1800
9. Mallet, L., Schüpbach, M., N'Diaye, K., Remy, P., Bardinet, E., Czernecki, V., Welter, M.L., Pelissolo, A., Ruberg, M., Agid, Y., et al.: Stimulation of subterritories of the subthalamic nucleus reveals its role in the integration of the emotional and motor aspects of behavior. Proceedings of the National Academy of Sciences **104** (2007) 10661–10666
10. Hadland, K., Rushworth, M.F., Gaffan, D., Passingham, R.: The effect of cingulate lesions on social behaviour and emotion. Neuropsychologia **41** (2003) 919–931
11. Volman, I., Roelofs, K., Koch, S., Verhagen, L., Toni, I.: Anterior prefrontal cortex inhibition impairs control over social emotional actions. Current biology **21** (2011) 1766–1770
12. Cordes, D., Haughton, V.M., Arfanakis, K., Carew, J.D., Turski, P.A., Moritz, C.H., Quigley, M.A., Meyerand, M.E.: Frequencies contributing to functional connectivity in the cerebral cortex in resting-state data. American Journal of Neuroradiology **22** (2001) 1326–1333
13. Chao, L.L., Lenoci, M., Neylan, T.C.: Effects of post-traumatic stress disorder on occipital lobe function and structure. Neuroreport **23** (2012) 412–419
14. Honey, C., Sporns, O., Cammoun, L., Gigandet, X., Thiran, J.P., Meuli, R., Hagmann, P.: Predicting human resting-state functional connectivity from structural connectivity. Proceedings of the National Academy of Sciences **106** (2009) 2035–2040
15. Adeli, E., Meng, Y., Li, G., Lin, W., Shen, D.: Multi-task prediction of infant cognitive scores from longitudinal incomplete neuroimaging data. NeuroImage (2018)
16. Mahjoub, I., Mahjoub, M.A., Rekik, I.: Brain multiplexes reveal morphological connectional biomarkers fingerprinting late brain dementia states. Scientific reports **8** (2018) 4103
17. Lisowska, A., Rekik, I.: Joint pairing and structured mapping of convolutional brain morphological multiplexes for early dementia diagnosis. Brain connectivity (2018)
18. Abdelnour, F., Voss, H.U., Raj, A.: Network diffusion accurately models the relationship between structural and functional brain connectivity networks. Neuroimage **90** (2014) 335–347
19. Bassett, D.S., Sporns, O.: Network neuroscience. Nature neuroscience **20** (2017) 353